STOCHASTIC SYNAPTIC PLASTICITY IN DETERMINISTIC aVLSI NETWORKS OF SPIKING NEURONS

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Summary

Stochastic learning solves the stability-plasticity problem (Fusi et al., 2000a) but raises new issues related to the generation of the proper noise driving the synaptic dynamics. Here we show that a simple, fully deterministic, spike-driven synaptic device can make use of the network generated variability in the neuronal activity to drive the required stochastic mechanism. Randomness emerges naturally from the interaction of deterministic neurons, and no extra source of noise is needed. Learning and forgetting rates of the network can be easily controlled by changing the statistics of the spike trains without changing any inherent parameter of the synaptic dynamics.

Introduction

General considerations counterposing memory stability and the need to acquire information from every stimulus (plasticity) led to the conclusion that synaptic plasticity should be controlled by one or more internal thresholds that separate a discrete set of stable synaptic states (Fusi et al., 2000a; Fusi, 2001). In this scenario, long term modifications (LTM) are expressed as transitions to different stable synaptic states. Networks learning and forgetting rates are directly related to the mean fraction of synapses that make a transition following each stimulus presentation: small fractions mean slow learning and high memory capacity (slow forgetting), while high fractions correspond to fast learning of novel stimuli and fast forgetting of the past experience (Amit and Fusi, 1994; Brunel et al., 1998). A simple unbiased local mechanism that selects which synapses are to be changed is stochastic learning: at parity of pre and post synaptic activities (to be encoded), transitions occur with some probability. Following each stimulus

presentation, this stochastic mechanism allows each synapse to decide whether to change or not and, without knowing what the other synapses are doing, to preserve in average the total fraction of updated synapses. Moreover slow learning can be easily achieved since the transition probabilities can be so low that the mean number of modified synapses is even smaller than 1 (Fusi, 2001). This approach moves the problem to the generation of the proper noise to drive the synaptic dynamics. The spike-driven synaptic model proposed in (Fusi et al., 2000a) exploits the variability in the neural activity to drive the stochastic mechanism: the source of randomness is in the spike emission process of the neurons and small transition probabilities are easily achieved because the long term modifications are based on the coincidence of events which are relatively rare (fluctuations in the pre-synaptic spike train and in the post-synaptic depolarization). We show here that these rare events can be the result of the collective dynamics of the fully deterministic network in which the pre- and post-synaptic neurons are embedded.

Methods

The network

In order to prove that a small neural network can generate the proper stochasticity to drive the learning mechanism, we used a VLSI network of 21 neurons which has been designed and produced in Roma by E. Chicca and D. Badoni (Chicca, 1999)[1]. The network is composed of 21 integrate-and-fire neurons, 14 of which are excitatory and the remaining 7 are inhibitory. Each neuron is randomly connected to a third of the other neurons in the network and the disordered pattern of connectivity contains the only randomness intentionally introduced in the design of the chip. Only excitatory neurons are connected amongst themselves by dynamical synapses, all the other connections are fixed. In our study we focused only on the network behavior emerging from excitatory interactions and the inhibitory population has been kept silent throughout all the tests.

The neuron

The implemented neurons are based on the schematics proposed by Mead (Mead, 1989) and can be considered as linear integrators with a rigid

[1]This latest implementation, LANN21b has been realized in CMOS technology, AMS $0.6\mu m$, chip area: 3.2 mm x 3.2 mm. The previous version, LANN21a has been tested in (Fusi et al., 2000b).

lower bound limiting the neurons' depolarization from below and an upper threshold θ for spike emission. Following a spike emission the depolarization is reset to some value and the neuron starts again to integrate the input current. The total current charging (or discharging) the neuron's capacitor is made of 4 components: the excitatory and inhibitory synaptic currents, the current injected from outside the chip and a constant leakage. Networks made of this kind of neurons are known to exhibit an interesting and rich phenomenology and can be used as associative memory devices (Fusi and Mattia, 1999).

The synapse

The synaptic dynamics can be fully described in terms of a single internal analog variable which is stored as a voltage across a capacitor. On long time scales and in the absence of any stimulation, a refresh mechanism makes the device bistable: voltages above some threshold θ_s are attracted towards the maximum value that correspond to the potentiated state, whereas lower voltages simply decay linearly to the depressed state. The synaptic efficacy (i.e. the evoked potential on the post-synaptic neurons) depends on whether the internal state variable is above or below θ_s. The two possible values can be chosen arbitrarily, making it possible to have a dynamical internal variable whose modifications do not affect the post-synaptic neuron (when the synaptic efficacy of the potentiated state is identical to the synaptic efficacy of the depressed state).

The bistability of the internal state variable guarantees that the memory of whether the synapse is above or below the threshold can be preserved indefinitely. Pre-synaptic spikes act as a trigger to change the synaptic state: upon the arrival of a pre-synaptic spike the synapse is pushed either up or down depending on whether the depolarization of the post-synaptic neuron is above or below some other threshold θ_V. If enough changes accumulate and the internal synaptic threshold θ_s is crossed, then the synapse makes a transition to a different stable state. Otherwise it returns to the state previous to the stimulation. When a stimulus to be encoded is imposed to the network, those synapses that are in the depressed state and see elevated pre and post-synaptic activity, tend to be driven towards the threshold. Only a fraction of them will eventually cross it and make a transition to the stable potentiated state. These synapses are essentially selected by the random fluctuations in the neuronal activity. This mechanism and the electronic implementation are described in details in (Fusi et al., 2000a). The learning process can be studied analytically given the transition probability as a function of the pre and post synaptic activities

(Amit and Fusi, 1994).

Observables

The depolarization of three excitatory neurons and the analog internal variable of the three synapses connecting the three neurons in a loop are directly accessible for measurement. The spikes emitted by every neuron are also readable. The input to the network is provided by 4 currents: three of them are injected in the three neurons of the loop and the last current is distributed to all the other excitatory neurons. To characterize the network behavior we focused on two quantities: one measuring the amount of disorder generated by the network, and the other being related to the degree of synchronization between spikes emitted by different neurons. The first quantity is the mean coefficient of variability (CV) of the inter-spike intervals (ISIs) averaged across all the excitatory neurons of the network. The second is the network cross-correlation at zero lag (i.e. the variance across time of the instantaneous fraction of neurons that fire within a short time interval).

To study the synaptic dynamics we measured the transition probabilities. Following each stimulus presentation, a fraction of those synapses connecting neurons with the same activity (i.e. encoding the same information) make a transition to a different state. This fraction of synapses is an estimate of the probability that a synapse makes a transition given a particular activity of the pre and post synaptic neurons. In order to estimate this probability we set all the synapses to one of the two states (e.g. the depressed state) and we stimulate all the neurons of the network in the same way, all the time. We then measure the first passage time (FPT), i.e. the first time a synapse makes a transition to a different state. As soon as all the observed synapses made a transition a trial is completed: we reset the synapses and we start again measuring the FPT. By repeating this procedure many times, we estimate the transition probability in a typical single presentation of a stimulus. For instance, if the mean FPT is 50s and the typical stimulus presentation is 0.5s, then the transition probability is 0.01, because, in average, the synapse would make a transition only in 1 presentation out of 100. Although the internal state is actually modified

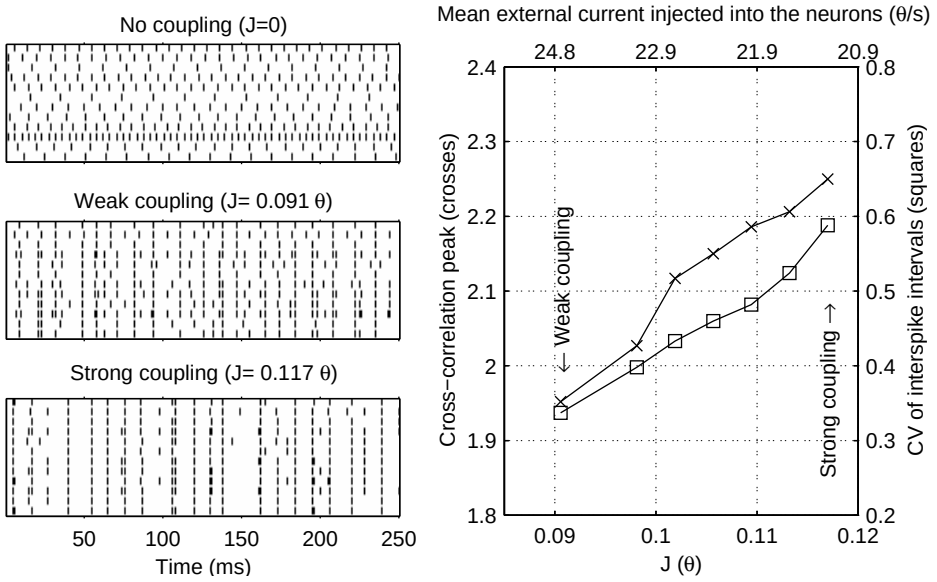

Figure 1: Network activity as a function of the mean coupling between neurons. Left: Spike rasters of 12 neurons for three values of synaptic coupling (from top, in units of the spike emission threshold $J = 0$, $J = 0.091\ \theta$, $J = 0.117\ \theta$). Right: the mean coefficient of variability (CV) of the inter-spike intervals as a function of the synaptic coupling J. The external current that drives the neurons is reduced to compensate for the increase in the synaptic current and hence to keep constant the mean firing frequencies of the neurons (always around 100 Hz). The network interactions produce a variability which is always accompanied by synchronicity (see also (Fusi et al., 2000b; D'Andreagiovanni et al., 2001)).

during stimulation, the synaptic efficacy is kept fixed in our tests. In a more realistic situation a change in the synaptic efficacy would produce a feedback on the network activity that in turns would modify the transition probabilities. These effects will be studied in another work. Here we assume that learning is slow enough not to affect too much the network dynamics in a single stimulus presentation. The parameters are actually set to have transition probabilities that are compatible with this hypotheses.

After estimating the transition probabilities we change the global parameters of the network (mean synaptic efficacy and mean input current) and we start the measuring procedure again. The currents to the three neurons connected by the observed synapses are tuned to keep the mean firing frequency (i.e. the activity to be encoded by the three observed synapses) always constant during the exploration of the space of neural and synaptic parameters (see also below).

Results

The functional noise generated by the network

We first show that the statistics of the spike trains generated by our network is good enough to drive the synaptic dynamics as expected by the theory of stochastic learning (Amit and Fusi, 1994). A constant current is injected in all the excitatory neurons. The activity produced by this external drive plus the recurrent interaction is supposed to imitate the activity of a stimulated population of neurons. Since the network is small, we assume that all the excitatory neurons belong to the population of neurons that are directly stimulated. The uniform pattern of activity induced by the stimulus is what should be encoded in the synaptic structure. All the neurons encode the same activity (mean firing rate), and hence, all the synapses connecting the excitatory neurons are supposed to undergo the same long term synaptic modifications.

In Fig. 1 we present the spike rasters of 12 excitatory neurons of the network, for three different values of the synaptic coupling and the external current, at the same average rates. If the network is uncoupled (the

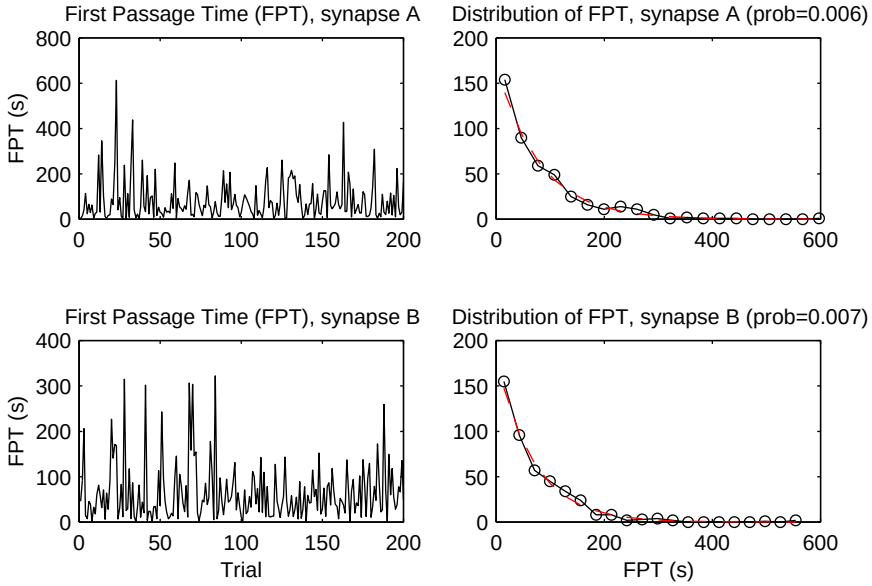

Figure 2: First passage time (FPT) for two synapses (synaptic coupling $J = 0.117\ \theta$). Left: FPTs in 200 trials for two synapses. At the beginning of every trial the two synapses are reset at the same time. Right: Distribution of the first passage time (solid circles connected by lines) and the predicted Poisson distribution (red dashed lines).

synaptic efficacies are set to 0) the neurons fire quite regularly when driven by an external constant current, indicating that the electronic noise that is always present in aVLSI devices has a negligible effect on the neuronal dynamics. As already noticed in (Fusi et al., 2000b), when the synaptic coupling increases, the network starts to be affected by the disorder of the connectivity pattern, and the neurons fire more irregularly. The external current is decreased to compensate for the increase in the synaptic current and to keep fixed the network global activity. The increase in the variability of the inter-spike intervals is accompanied by an increase in the degree of synchronization between different neurons (Fig. 1). This phenomenology is already known (Fusi et al., 2000b) and has been studied extensively in (D'Andreagiovanni et al., 2001).

The stochastic synaptic transitions

We now analyze, in this simple situation, what happens to the dynamic synapses: the transition probabilities are estimated as explained in the

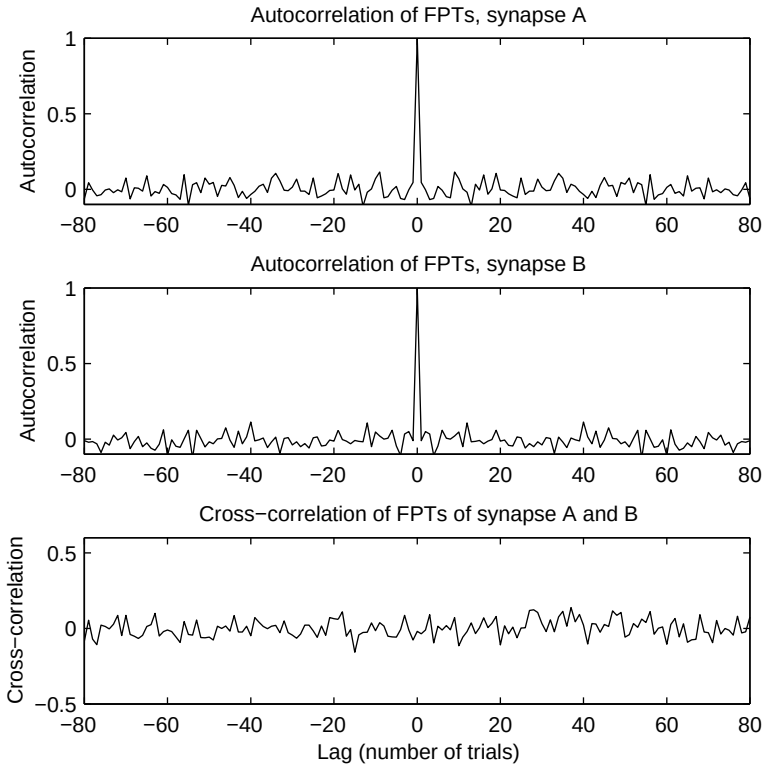

Figure 3: Auto and cross-correlograms of the first passage times for the two synapses of Fig. 2. The two synapses are clearly uncorrelated and the FPTs do not show any temporal structure (the auto-correlograms are flat, except at 0 lag).

Methods. The synapses behave stochastically, as expected, and the FPTs resemble the time intervals of rare events that are distributed as in a Poisson process (see Fig. 2). The variability is entirely generated by the network that works as a large diffused source of noise: no extra source of stochasticity is needed. The large size of the noise generator is also reflected by the fact that the first passage times can be several orders of magnitude longer than the longest inherent time constant of the synaptic device ($\sim 100ms$). Interestingly the kind of variability generated by

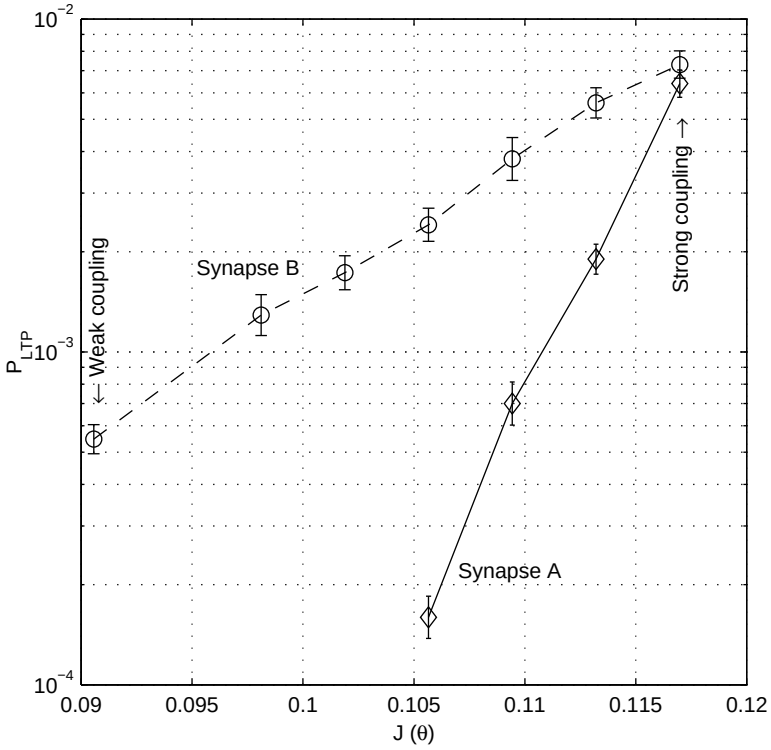

Figure 4: Probability of inducing a transition in a single stimulation lasting 0.5 s for two synapses as a function of synaptic coupling (in units of the spike emission threshold). The mean external current injected into the excitatory neurons is tuned to keep the mean firing frequency (i.e. the activity to be encoded) fixed. The corresponding neural activity of the network is illustrated in Figure 1. Low transition probabilities (slow learning, and good storage capacity) are achieved in the least synchronous states (weak couplings); whilst high transition probabilities (fast learning and fast forgetting) correspond to the most synchronous states (strong couplings). For uncoupled neurons (not shown in the plot) the transition probabilities are zero since there is no variability in the inter-spike intervals of the pre-synaptic neuron.

the network is such that the stochastic transitions of different synapses are not correlated. This is already clear from the FPTs of two synapses shown in Fig.2. The auto- and cross-correlograms of Fig. 3 give a further evidence that 1) the FPTs as a function of trial number are delta-correlated, and hence each FPT does not depend on what happened in the previous trials. The statistics of the FPTs as random variables is stationary; 2) the crossing of the synaptic threshold for synapse A does not affect the stochastic process driving synapse B: indeed the FPTs of the two observed synapses are uncorrelated, even if the transition probability is about the same for the two synapses.

Network controlled learning and forgetting rates

In our tests we kept constant the network mean frequencies on purpose, to expose the dependence of the transition probabilities on the other statistical properties of spike trains emitted by the pre and the post synaptic neurons. In particular here we show that the synaptic device is rather sensitive to the variability and to the amount of synchronicity in the network. This would nicely fit a scenario in which the mean frequency encode the information about the stimulus that to be memorized and the other statistical properties provide a triggering signal for learning.

When the network is uncoupled the synapse behaves in a deterministic way since there is no noise in the system: for a given firing frequency of the neurons either it always makes a transition or it never reaches the threshold. We chose the parameters in such a way that the synapse can not make a transition in the deterministic case, no matter how long the stimulation time is. As the synaptic coupling increases, the neuronal activity becomes more variable and synchronous, changing dramatically the transition probability (Fig. 4). For weak network coupling the synapse makes transitions with probabilities that can be as low as 10^{-4}. As a consequence thousands of presentations of the same pattern would be required to leave a memory trace in the synaptic matrix (Brunel et al., 1998). This is the ideal situation for optimizing memory capacity (Amit and Fusi, 1994). On the other hand, as synchronicity increases, the transition probabilities increase, making learning much faster, at the expenses of memory capacity.

Conclusion

We have shown that a small aVLSI network is able to produce the proper noise for driving the stochastic synaptic dynamics as expected in a slow

learning scenario. The variability results from the random connectivity of the network and no noise is injected. Even in this simple and clearly not optimal case where the stochasticity emerges from only excitatory interactions, slow learning, that would require thousands of 0.5 s presentations of the same stimulus, is easily achieved with inherent time constants as short as 100 ms (we did not consider inhibition which is shown to play a major role in increasing the variability in (D'Andreagiovanni et al., 2001)). Moreover the learning speed can be readily controlled by the statistics of the network activity. One simple lever of control is the rates provoked by the stimuli, however the synapse is rather sensitive also to the variability in the inter-spike intervals and to the degree of synchronization of the spike trains, at parity of mean frequencies. This means that the network can easily and quickly switch from a single shot learning modality to slow learning (and optimal storage capacity), without changing any parameter of the synaptic dynamics. This is yet another advantage of transferring the load of generating stochasticity to the network dynamics.

Acknowledgements

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